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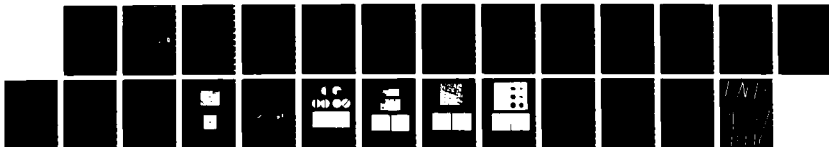
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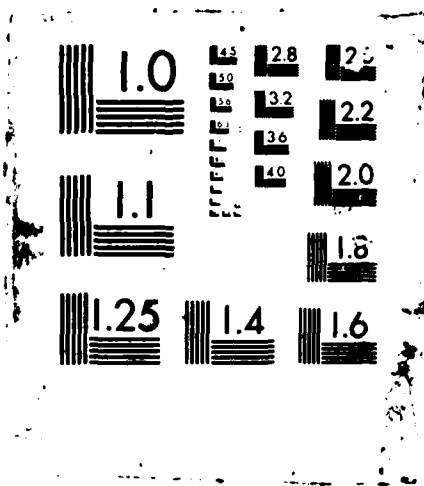
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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This report describes the research conducted through September 1986 on the investigation of vision systems for aerial scenes. The projects reported on include: 1) Defining Measures Related to Perceptual Properties 2) Texture Operators and their Application to Vision Systems 3) Structure of Vision Systems for Aerial Scenes and 4) General Purpose Spatial Operators.

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The Integration of Spectral and Spatial
Analysis for Land Use Classification
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1.0 Introduction

In this report we describe our work on developing improved computer vision systems for aerial scenes. Our research efforts included research on developing a hierarchical vision system for aerial scenes, comprehensive vision operators, detection of linear features, developing theory for defining new measures which reflect perceptual properties, developing operators and measures for characterizing texture patterns and evaluating the theory on aerial scenes.

A computer vision system can be conceptualized as being composed of vision operators, an inferencing system, and a knowledge base of models and facts. The vision system should label and describe the objects, subobjects and relationships in the scene. The vision operators are used to extract image cues from the image. The role of the inferencing system is to sequence or select the models in the knowledge base, match the extracted image cues against the models, resolve conflicts and track the inferences. In creating a vision system a number of problems must be addressed. These are: the interaction between the vision operators and the inferencing system, the selection and adequacy of the vision operators, the method of forming an optimal global interpretation of the scene, and the integration of system modules and data structures so that the system can be improved as additional knowledge about the scene becomes known.

The quality of the measurements or image cues obtained by the vision operators is a key to system performance. If the operators return reliable information with a rich descriptive vocabulary, then the vision system is greatly enhanced.

2. General Purpose Operators

There are three important issues related to operators for a computer vision system. The first is that the operators must be widely applicable or general purpose; secondly the operators must have a rich descriptive vocabulary; thirdly the operators must be suitable for obtaining image cues from intermediate levels of the scene hierarchy. We feel that the approach to be pursued first is to model Gestalt principles of perceptual organization. These approaches can aid in building a geometric reasoning system. We are interested in developing general purpose operators which measure perceptual properties. These operators offer advantages in their descriptive vocabulary over traditional operators. They can also be utilized at intermediate levels of the scene hierarchy.

The present capabilities of texture algorithms severely limit their usefulness in vision systems. Present algorithms utilize supervised training methods to select measures. Many times the measures selected may be correlated and may not even be measuring relevant information about the scene structure. One needs a higher level of proficiency in texture algorithms. One would like to avoid supervised learning. One desires a metric to correctly gauge the proximity of measurements in measurement space when the areas from which the measurements are obtained are close perceptually. Theoretical results directed towards solving this problem are reported in Vasquez[1984]. The solution to this problem would allow one to obtain better results utilizing clustering or region growing methods to segment the image. At the higher levels of analysis this would ensure the vision system is robust. For example, residential scenes will all vary to some extent. It is required to have operators which reflect the perceptual properties of these areas in order to label the different areas correctly. The most desirable situation would be for operators to characterize scenes using the same perceptual properties utilized by humans. Examples of such properties would be symmetry[Marr 1982, Julesz 1969], periodicity[Mach 1959], uniformity[Wertheimer 1958], edge detection and corner detection [Hubel and Wiesel 1968]. This would be a step in the direction of providing a richer descriptive vocabulary for the operators related to human perceptual properties. If these operators could be developed, they would have great utility in vision systems.

It is our belief that these operators can be based upon algorithms previously applied in various forms to texture patterns. We will show later in this report that the operators have broader application than to texture patterns.

3. Theory of Measurement Definition.

The framework is based on the concepts of a perceptual transform, a perceptual space, a measurement space, a measurement transform, a measurement space, and a similarity transform relating how similar the measurement space and the perceptual space must be.

Let W be the set of all possible textures and let w denote an element of W .

Definition 1. The perceptual transform, $T_p(w)$ is an n -dimensional vector of visual features "computed" by the human perceptual system. It maps the set W into the perceptual space, P_s .

Definition 2. Two textures w_1 and w_2 are visually distinct if and only if $T_p(w_1)$ is not equal to $T_p(w_2)$, that is, if w_1 and w_2 are mapped into different points in the perceptual space, P_s .

Definition 3. A measurement to transform, T_m represents the k -dimensional vector of measures computed from a texture where each component of T_m is a texture measure. T_m maps elements of W into a k -dimensional measurement space, M_s .

Definition 4. A similarity transform, T_s maps the points of P_s into the points of M_s . **Definition 5.** The set of measures defined by $T_m(w)$ is said to match with similarity T_s the human perceptual ability if $T_s(T_p(w)) = T_m(w)$ for all w in W .

This definition establishes the goal a measurement definition problem, namely, given T_s , define the measurements such that:

$$T_s(T_p(w)) = T_m(w). \quad (1.)$$

for all w in W .

Theoretically, the "best" set of measures would seem to be those defined when T_s is the identity transform. This would force the texture measures to be the same as the features used by the human perceptual system.

There are, however, two good arguments against attempting this. First, what may be optimal for humans, computationally, may be very suboptimal for computers. Secondly, the present state of perceptual psychology and neurophysiology makes such an objective practically impossible.

Rather, the appropriate course of action would seem to be to determine in what ways we would like our early vision operators to mimic human performance. Once this is done, one can define a T_s which captures these essential characteristics so that an appropriate set of measures can be identified.

Let us present the ways we believe texture operators should mimic human perceptual performance.

1. Texture measures should be able to discriminate any two visually distinct textures.
2. The texture measures should be such that a norm on the measurement space will preserve human judgements about the similarity of textures. This comes from the realization that one of the most important task of any early vision operator is to aid in segmenting the image.
3. The dimensionality of the measurement space should be as small as possible.

These desires translate into a set of requirements on T_s . These requirements are as follows:

1. T_s should be one-to-one.
2. If w_1 and w_2 are any two textures in W then:

$$N(T_m(w_1), T_m(w_2)) = N_p(T_p(w_1), T_p(w_2)). \quad (2.)$$

where N is a norm on the measurement space and N_p is a norm on the perceptual space.

3. For each measurement m_i , a component of T_m , there should be two visually distinct textures, say w_1 and w_2 , such that $m_i(w_1)$ is not equal to $m_i(w_2)$.

A quick analysis will show that requirements 1 and 2 on T_s are redundant since requirement 2 insures requirement 1. Hence, there is really only one requirement on T_s to drive the definition

process. The key to using this requirement is having a perceptual norm, N_p , that for a set of texture pairs can give a relative ranking as to how visually distinct each pair is as compared to the others. One such ranking scheme is the law of comparative judgement (LCJ) developed by Thurston [1927].

Given this perceptual ranking scheme, assume we have s texture pairs, $p_i = (w1i, w2i)$, $i=1, \dots, s$. A perceptual experiment can be performed [Zobrist and Thompson 1975], so that the law of comparative judgement can be used to give a ranking r_{pi} to each of the texture pairs p_i , where each r_{pi} , $i=1 \dots s$, is a positive real number.

For each of the s texture pairs, requirement 2 demands that

$$N(T_m(w1i), T_m(w2i)) = r_{pi}. \quad (3.)$$

However it is unlikely that any measurement set can be defined so that Eq. 3 is exactly satisfied for $i=1, \dots, s$. Rather it seems more probable that for each possible measurement set $T_m(w)$ we will have

$$N(T_m(w1i), T_m(w2i)) = r_{pi} + e_i. \quad (4.)$$

where e_i represents an error term. Therefore, the more reasonable approach is to pick the measurement set which minimizes the sum of squares of the error terms, i.e., a least-squares fit.

To integrate requirement 3 into the definition process requires the following procedure be followed in defining the measures. First solve for one measure. You do not solve for a second measurement until a visually distinct texture pair has been found that cannot be discriminated by this one measure. Given the existence of such a texture, one then solves for two measures, etc.

To use this formal definition process requires (a) a perceptual ranking experiment be performed; (b) the LCJ be applied to the experimental data; (c) a least squares procedure (LSP) be implemented to solve for the measures; (d) an assumption about the form for the norm, N , on the measurement space, and about a functional form for the measurements; and (e) a good texture synthesis procedure for generating texture pairs used both in the experiment and in establishing whether additional measures are needed.

Given the assumptions required to perform the least squares analysis, this measurement definition process assures that the measurements defined are such that there exists a transformation T_s in the class of transformations satisfying the above requirements where

$$T_s(T_p(w)) = T_m(w). \quad (5.)$$

for all textures w comprising the texture pairs used in the perceptual experiment. If these textures are representative of the universe of textures, then the goal of the measurement definition process as given in Eq. 2 is satisfied.

Using this Formal Method on a Simplified Problem

To test this formal definition process, it was employed on a simplified problem. The simplifications were that the texture pairs used in the perceptual ranking experiment were generated using only one texture synthesis method and that these textures contained only three gray levels. Limiting the number of gray levels markedly reduces the number of texture pairs that must be considered to solve for the measurements. Using only one synthesis method provided other simplifications useful in the least-squares fitting of the data.

The experimental procedure used with the law of comparative judgement was the method of paired comparisons. This experimental procedure requires that each stimulus (texture pair) be compared with all the other stimuli. Hence to perceptually rank the twenty-two texture pairs requires 231 paired comparisons be made.

To make these comparisons, 231 display boards were prepared. The 231 boards were presented to 18 different observers, each observer seeing the boards on two occasions with the order of presentation being reserved on the second viewing by each observer. The question asked was "which of these two texture pairs contains the more visually distinct textures?"

Since the results when only one measure was defined were unsatisfactory, we solved for two measures. The residual plot indicates an improvement but indicates that still more measures might be

necessary. We call these measures M12 and M22. Attempts were made to solve for three and then four measurements. However no marked improvement in the quality of fit occurred. The reason for this can be explained by making two observations. First every measure that is defined by this method requires $3 \times 3 = 9$ coefficients be estimated. Thus when one attempts to solve for first one, then two, then three and then four measures, 9, 18, 27, and then 36 coefficients must be estimated, respectively. Since there are only 22 different texture pairs whose relative rankings are being used to drive the estimation process, attempting to solve for more than two measures makes more unknowns than there are equations constraining these unknowns. Thus, it seems reasonable that no improvement is noted.

It is of interest to note that the measures, M12 and M22, defined using the formal measurement definition process, appear functionally equivalent to the contrast measure and symmetry measure whose definitions arose from the consideration of periodic textures. That is, measure M12 can gauge the presence or absence of nonzero off diagonal elements, the job the contrast measure was picked to do in the analysis of periodic textures. Further, measure M22 can be used to gauge the symmetry or asymmetry of a GLC matrix. This was demonstrated by comparing the spectrums of measure M11 and the contrast measure on a number of images. Both clearly indicate periodic structure of the texture patterns in the images. In a like manner the spectrums of the symmetry measure and a simple function of M22 also appear very similar, each indicating the direction of maximal symmetry and asymmetry of the pattern in the image. The simple functional for of M22 which is used is

$$f(M22(d,T)) = 1/2 M22(d,T) + M22(-d,T) / 2$$

In summary, the primitive measures defined using two completely different approaches to the definition problem appear functionally equivalent. This suggests the validity of the theoretical approach to measurement definition. It is also interesting to note that these measures appear to form the basis for truly general purpose operators.

4. GLC Matrices and Tiling Theory.

For notational convenience we often let $u = (x,y)$ denote a two dimensional vector in E^2 the Euclidean plane.

Definition 1. A tile T is a subset of the Euclidean plane, E^2 , that is a closed topological disk.

Definition 2. A plane tiling is a family of tiles $\tau = \{T_i \mid i=1,2,\dots\}$ that covers the plane without holes or overlaps. The tiling is monohedral if each tile in the tiling is a single prototile.

Definition 3. A function s that maps E^2 into E^2 is called an isometry or congruence transformation if it maps E^2 onto itself and if x, y are elements of E^2 then $N(x,y) = N(s(x), s(y))$ where N is the standard Euclidean norm. That is, an isometry is a mapping which preserves distance.

An isometry is a symmetry of a tiling if it maps every tile of a tiling into another tile of the tiling. If there exist at least two translation symmetries in nonparallel directions, then the tiling is said to be periodic. Let these directions be given by unit vectors a and b . The set of all translations $\{na + mb\}$ forms a lattice which give the vertices of a parallelogram tiling.

Definition 4. The tiles of the parallelogram tiling are known as the period parallelogram.

These concepts are extended to texture patterns by considering the gray levels within the tile.

Definition 5. A primitive is $\{T,f\}$ where T is a tile and f is a function that maps T into the nonnegative real numbers.

We call f a painting function which gives the tile a pattern.

Definition 6. A set of primitives $\{T_1,f_1\}, \dots, \{T_n,f_n\}, \dots$ is admissible if the set of prototiles $\{T_1,T_2,\dots,T_n\}$ admits a tiling of the plane.

Each element $\{T_i,f_i\}$ is called a unit pattern. T_i is called a unit tile.

Definition 7. A gray level cooccurrence (GLC) matrix, $S(d,T)$, is a matrix of estimated second-order probabilities where each element $S(i,j,d,T)$ is defined by

$$S(i,j,d,T) = \frac{O(u | u, u+d \in T, g(u)=i, g(u+d)=j)}{O(u | u, u+d \in T)}$$

where T is a tile, $S(i,j,d,T)$ is estimated from the restriction of the picture function $g(x)$ to T , and where O denotes the order of the set.

It is frequently convenient to consider $d = (\delta x, \delta y)$ not in cartesian form but rather in a polar form $d = (r, \theta)$ where $r = \max(\delta x, \delta y)$ and $\theta = \arctan(\delta y / \delta x)$.

Definition 8. A primitive measure, $M(d,T)$ is a real valued function whose independent variables are the elements of a GLC matrix, $S(d,T)$.

An example of a primitive measure is the contrast measure, $C(d,T)$, defined by

$$C(d,T) = L^2 - \sum_{i=0}^L \sum_{j=0}^L (i-j)^2 S(i,j,d,T)$$

where L is the number of gray levels. The contrast measure varies from 0 to L^2 .

Definition 9. The spectrum, $Q(M,T,R)$, of the primitive measure $M(d,T)$ is $M(d,T)$ evaluated for all d in R where R is a region of E^2 containing the origin.

For example, the circular spectrum of the contrast measure $C(d,T)$, is $C(d,T)$ evaluated for all d in R where R is the set of all points $(\delta x, \delta y)^T$ such that $\delta x^2 + \delta y^2 \leq r^2$.

Definition 10. An spectral measure, $K(M,T,R)$, is a real valued function whose independent variables are the elements of the spectrum $Q(M,T,R)$ where $M(d,T)$ is a primitive measure.

No single GLC matrix can characterize a texture. Rather, a number of GLC matrices is required. This means that to characterize the structure of an image one will need spectral measures derived from the spectra of primitive measures.

5. Periodicity Measures.

One set of patterns that one would desire to analyze are periodic textures. Our work on periodic textures motivated the formulation of a tiling theory model of texture [Conners and Harlow 1980]. One should also note that periodicity is a perceptual property readily perceived by humans. In Conners and Harlow [1980] it was shown that to characterize periodic textures one need only determine a period parallelogram unit pattern. This requires that one determine two vectors a and b which specify the period parallelogram unit pattern, Figure 1.

The GLC matrices can detect periodicity. Suppose in direction d the pattern has periodicity t . If d is a unit vector then one has the following properties.

1. The matrices $S(nd,T)$ for $n = 1, 2, \dots, t-1$ have nonzero off diagonal elements.
2. The matrices $S(ntd,T)$ for $n = 1, 2, \dots$ are diagonal matrices with no nonzero off diagonal elements.
3. The GLC matrices are periodic in direction d with periodicity t . That is, $S((nt+m)d,T) = S(md,T)$ for $m, n = 1, 2, \dots$.

This implies that a measure such as the contrast measure should reflect the periodicity of patterns. The contrast measure should be zero when the GLC matrix is diagonal and nonzero otherwise.

The complete analysis of a periodic patterns requires determining the size and shape of the unit tile as was done above. In addition, the analysis requires determining the painting function of the unit cell. This means the correct placement of the unit cell must be determined. We feel the one humans

would select is the placement where the object is centered in the cell. This is equivalent to placing the unit tile so that the pattern is symmetrical. One might note that symmetry is a perceptual property [Julesz 1969] and psychologists have long thought the property to be important in figure/ground determination where the symmetrical pattern would be the figure. Therefore, the problem can be reduced to locating a symmetrical pattern which will then completely determine $\{T, f\}$ where T is the parallelogram tile and f is the painting function. The GLC matrices can be utilized to determine symmetry.

6. Symmetry Measures.

Definition 1. A function f defined on a tile T is symmetric about the x axis if:

1. If $(x, y) \in T$ then $(-x, y) \in T$ and
2. if $(x, y) \in T$ then $f(x, y) = f(-x, y)$.

Definition 2. A function f defined on a tile T is symmetric about the origin if:

1. If $(x, y) \in T$ then $(-x, -y) \in T$ and
2. if $(x, y) \in T$ then $f(x, y) = f(-x, -y)$.

The coordinate system to which these definitions refer need not be orthogonal but can be a local coordinate system defined on the period parallelogram, Figure 1. In this local coordinate system the x axis is aligned with the a vector and the y axis is aligned with the b vector. This is the coordinate system of interest in the following results.

Result 1. If a function defined on a tile T is symmetric about both the x and y axis, then it is symmetric about the origin. The converse is not necessarily true.

Let us now relate these concepts to GLC matrices. In the following results we assume that $\{u | u, u+d \in T\}$ is not the empty set.

Result 2. If a function f defined on a tile T is symmetric about the x axis of a local coordinate system, then the GLC matrix $S(d, T)$ is a symmetric matrix when d , defined in the local coordinate system, is equal to $(0, \delta y)$.

Result 3. If a function f defined on a tile T is symmetric about the y axis of a local coordinate system, then the GLC matrix $S(d, T)$ is a symmetric matrix when d , defined in the local coordinate system, is equal to $(\delta x, 0)$.

Result 4. If a function f defined on a tile T is symmetric about the origin of a local coordinate system, then the GLC matrix $S(d, T)$ is a symmetric matrix when d is defined in the local coordinate system.

A typical GLC matrix is not symmetric. This then leads us to the following hypotheses:

Hypothesis 1. If a function is defined on a parallelogram tile T is asymmetric about the x axis of the local coordinate system aligned with the parallelogram, then there exists a displacement d of the form $d = (0, \delta y)$ where $S(d, T)$ is an asymmetric matrix.

Hypothesis 2. If a function is defined on a parallelogram tile T is asymmetric about the y axis of the local coordinate system aligned with the parallelogram, then there exists a displacement d of the form $d = (\delta x, 0)$ where $S(d, T)$ is an asymmetric matrix.

Hypothesis 3. If a function defined on a parallelogram tile T is asymmetric about the origin of the local coordinate system aligned with the parallelogram, then there exists a d defined in terms of this same coordinate system such that $S(d, T)$ is an asymmetric matrix.

Experimental results obtained so far indicates that these hypothesis are true for data obtained from images. The following results have been shown analytically to be true.

Result 5. Suppose f is a function defined on a parallelogram unit tile T specified by vectors a and b and the unit pattern $\{T, f\}$ is asymmetric about the x axis of the coordinate system. Let $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ be a set of points such that $f(x_i, y_i)$ is not equal to $f(x_i, -y_i)$. Without loss of generality let (x_1, y_1) be such that $y_1 > y_i$ for $i = 2, \dots, n$. Also $0 < y_1 \leq \|b\|/2$ where b is the vector parallel to the y axis in the parallelogram coordinate system. Then if $d = (0, y_1 + (\|b\|/2) - 1)$, the GLC matrix $S(d, T)$ is an asymmetric matrix.

There is a similar result for the y axis.

Result 6. Suppose f is a function defined on a parallelogram unit tile T specified by vectors a and b and the unit pattern $\{T, f\}$ is asymmetric about the y axis of the coordinate system. Let $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ be a set of points such that $f(x_i, y_i)$ is not equal to $f(-x_i, y_i)$. Without loss of generality let (x_1, y_1) be such that $x_1 > x_i$ for $i = 2, \dots, n$. Also $0 < x_1 \leq \|b\|/2$ where b is the vector parallel to the y axis in the parallelogram coordinate system. Then if $d = (0, x_1 + (\|b\|/2) - 1)$, the GLC matrix $S(d, T)$ is an asymmetric matrix.

These results indicate how the analysis might proceed to determine the correct location of the unit tile might proceed. First, one must check GLC matrices to determine if they are symmetric. In addition, one must consider d of the form $(\delta x, 0)$ and $(0, \delta y)$, where $0 < \delta x \leq \|a\| - 1$ and $0 < \delta y \leq \|b\| - 1$ where d is given in the local coordinate system aligned with vectors a and b .

The above discussion indicates a need for a measure to characterize the symmetry of a pattern in direction θ where $\theta = \arctan \delta y / \delta x$ when $d = (\delta x, \delta y)$. A measure which characterizes the symmetry of a GLC matrix is given by

$$U(d, T) = 2 - \sum_{i=0}^L \sum_{j=0}^L |S(i, j, d, T) - S(j, i, d, T)|.$$

where L is the number of gray levels. We call U the symmetry measure. U is large when the pattern is symmetrical in direction θ and U is small when the pattern is asymmetrical in direction θ .

7. Global and Local Analysis of Periodic Texture Patterns.

Let us now consider the utilization of these concepts to analyze textured objects.

First consider the tank farm scene in Figure 2. The initial step is to compute the contrast spectrum as shown in Figure 2. One then determines the local maxima in the contrast spectrum. We find the position and value of these maxima. The periodicities indicate the vectors a and b . Clearly, in this example they are in the horizontal and vertical directions. A tiling is then placed on the area which composes an edge to edge tiling of the area. The correct placement of the tiling remains to be determined. The placement of the tiling will specify the painting function of the unit tile. This is defined to be the location that creates a symmetric pattern in the unit tile. Next, we compute the symmetry spectrum which is computed using the symmetry measure. For each x, y position in the a vector direction and for each x, y position in the b vector direction one computes the symmetry measure as indicated in Result 6 of section 6. Bar measures in the a and b are computed on the symmetry spectrum. These measures will be a maximum in the desired position. The symmetry spectrum can be used to rank the symmetry and thereby select the correct position of the tile. The correct tile position is selected as the x, y position which creates a symmetrical pattern. This is shown in Figure 2.

Let us now consider how these operators might be utilized in a vision system. This involves a global to local analysis. The global analysis would require determining the vectors a and b which characterize the unit tile T and then determining the correct location which implies the painting function f since g the image function restricted to T defines f . This gives $\{T, f\}$ which characterizes the global properties of the pattern. The calculation for determining the unit tile T would proceed as indicated above utilizing the contrast spectrum. The correction location for T would be determined using the symmetry measure as indicated above. These are examples of intermediate level measures which could be used in the analysis hierarchy. Note that these measures characterize the pattern of interest

directly and are not inferred from a lower level in the hierarchy. Once $\{T, f\}$ has been determined the search for details would proceed to the next level in the hierarchy. Let us now turn consideration to detecting visual features of a different type.

8. Operators for Detecting Edges and Linear Features.

Recall that in the previous section we indicated how GLC operators could be used to characterize textured objects. This involved a global analysis to determine the unit tile which was determined by vectors a and b . A local analysis was then performed to determine the painting function. It is interesting to note that a distributed pattern such as a texture pattern requires a local analysis which is the type of analysis one expects to perform on a local object. Local objects are not characterized by a distributed texture pattern. In the past local objects were usually characterized by an edge detection or thresholding method which utilizes gray level differences or gray level clusters to determine objects or regions [Rosenfeld 1982, Riseman and Arbid 1977]. In this section we intend to generalize the concepts presented in the last section to include the ability to analyze edges and linear features. We intend to analyze these features when they are characterized by texture pattern differences as well as when they are characterized by gray level differences.

The techniques used in this development will be bar measures extracted from the contrast and symmetry spectrums. Recall, that the contrast and symmetry spectrums were utilized in the previous section to characterize texture patterns. A bar measure is a spectral measure which gives the average value over a bar shaped area of a spectrum. Figure 3 depicts the geometry. The methods developed are simple yet versatile. They can analyze texture patterns for global properties, characterize linear feature and characterize edges. They also provide an enlarged descriptive vocabulary for image cues.

Bar measures computed on the symmetry spectrum give a way to determine the symmetry/asymmetry of a pattern about an axis through the center of the circular shaped region T from which they are computed. The symmetry bar measure is high in a direction where the pattern is symmetrical. The symmetry bar measure is low in a direction where the pattern is asymmetrical. If all the bar measures are large, the pattern is symmetric about the center of the circle.

Bar measures on the contrast spectrum reflect the Gestalt principle of uniformity and proximity. This principle states that close and similar elements will be perceptually grouped together. For a given d , the contrast measure indicates the similarity of gray levels d units apart. If the patterns are similar, the contrast measure will be large. A contrast bar measure is the average contrast measure for a contiguous set of d 's in a given direction while lie in the circular spectrum. For a uniform pattern the contrast bar measure will be large while for a nonuniform pattern the contrast bar measure will be small.

In our calculations the spectrums for the contrast measure and the symmetry measure must be computed. The coordinates and values of minima in the spectra are determined and bar measures from these two spectra are computed. These entities can be easily computed from the spectra.

Let us now consider how the above principles can be applied to edge detection. Consider the images shown in Figure 4. The direction of an edge is traditionally [Rosenfeld and Kak 1982] defined to be $\phi = \arctan(g_y/g_x)$. For the vertical edge in Figure 4 the edge direction ϕ is 0 degrees. The contrast spectrum is shown in part (b) of the figure. The darker the gray level the lower the value of the contrast measure. The presence of an edge can be determined by examining bar measures which are perpendicular to each other. In this case the vertical bar direction has the highest average value of the contrast measure. A horizontal bar direction has the lowest average value of the contrast measure. The pattern is the most uniform in the direction $\theta = 90$ degrees, Figure 4 (d), which corresponds to the maximum in the contrast bar measure. This indicates the edge is in the direction $\phi = 0$ degrees.

There is another way to describe this edge. A vertical edge is maximally asymmetric about the y axis and symmetric about the x axis. That is, the pattern is symmetric in the $\theta = 0$ degree direction. The symmetry bar measures should provide another independent characterization of edges. Note that the symmetry and contrast measures are independent in that they measure different pattern characteristics. Part (b) of Figure 4 shows the contrast spectra and part (c) shows the symmetry spectra. Part (d) shows the contrast bar measure and part (e) shows the symmetry bar measure. Note that the vertical bar of the symmetry measure is a maximum in the $\theta = 90^\circ$ direction. This indicates the pattern is symmetrical

in the direction $\theta = 90$ degrees. Note that the minimum occurs in the $\theta = 0$ degrees which indicates the pattern is asymmetrical in this direction. The pattern is symmetrical about the x axis in this case. The edge direction ϕ is 0 degrees according to the traditional calculation. This is 90 degrees from the maximum in the symmetry bar measure. A calculation for an edge in any other direction would proceed in the same manner.

Now consider the corner region in Figure 4. Note that the symmetry spectrum has a maximum bar measure in the direction 45 degrees. The pattern is therefore symmetrical in this direction. This indicates the pattern is symmetrical about the 135 degree axis which characterizes the corner.

Now let consider detecting the edge when the difference between the two regions is a texture difference. Figure 5 shows an area where an edge exists between a forested area and a grassy area. Note that this difference is determined by a symmetry measure. The pattern is symmetrical in the $\theta = 90$ degree direction. This is reflected in the bar measures extracted from the E2 region. The symmetry bar measure in the $\theta = 90$ degrees direction has the maximum value. This indicates the direction of the edge is $\phi = 0$ degrees. Note, that the same methods work for textured regions as previously we applied to edges characterized by gray level differences.

Now consider the detection of linear features. Figure 6. shows an area with a road structure. Observe that in the region the symmetry bar measure is a maximum in the $\theta = 170$ degrees direction. This indicates the pattern is symmetrical in the $\theta = 170$ degree direction. This indicates the road is in this direction since the road pattern is symmetrical in the direction of the road. One might also desire to know the exact location of the road. This could proceed in a global to local manner. In this case one knows the road appears in the large circle. One could proceed to examine smaller circles interior to the large circle to more precisely locate the road. Figure 7 shows three smaller regions extracted from the same area. Part (a) shows the scene. Part (b) shows the contrast and symmetry spectra. Regions one and two are determined to contain the road structure while region three contains a forested area. The road direction is indicated by the maxima in the bar measures shown in part (c). The road is indicated to be in direction 170 degrees in R1 and R2 while the R3 bar measure indicates a road feature is not present. One could continue to examine smaller circles if a more accurate location is required.

9. Developing a Hierarchical Aerial scene Analysis System.

An important problem related to developing a vision system is to have operators that reliably return image cues appropriate for the later phases of processing. It is important to develop operators whose measures have meaning to human interpreters. This implies that the operators should measure some understandable perceptual property. Operators that measure perceptual properties should have a certain robustness. They should preserve perceptual similarity. This means that two similar areas in the scene, for example two residential areas, would be close in measurement space. Thus, the vision system should not make severe errors such as calling a residential area some disparate label such as commercial. It is also important to develop operators which extract image cues at intermediate levels in the scene hierarchy. This will relieve the inference system from undue dependence upon low level image cues. An example might be an operator that examines an area and determines if the image patterns are periodic. Such a determination might rule out commercial areas and indicate residential as a possible interpretation. The previous sections have indicated some approaches to developing operators with these properties.

The computer vision system we are developing is a hierarchical system where each level of the hierarchy corresponds to a particular level of detail in the scene. At any level the system considers only K_i objects. The K_0 objects give a gross classification of the scene while classification at level $i, i > 0$, gives a more detailed classification of the scene. The objects are generic objects and attached to each node of the hierarchy is a frame or schema for modeling the object [Harlow et. al. 86]. A key to the development of this system is to have operators able to characterize the object at any level. Our desire is to develop intermediate level operators for extracting image cues and thereby reduce the dependence upon low level image cues. If this can be done, then every level in the hierarchy can be treated similarly. At any given node one can directly operate on the scene data and transmit information to nodes on the level above or below the node. The frames at each node model complex objects which are in

turn composed of simpler objects forming a hierarchy of scene objects. Nodes higher in the hierarchy obtain image information and pass it down the hierarchy. Because the objects are generic objects they can provide global constraints on the scene. At each node in the hierarchy a context is provided and the number of objects to be located in this context is limited, figure 8. Also there should be available at the node information provided by the context as to locations of the subobjects of the object. This can be important in aerial scenes where the possible objects of interest that can occur in a scene may be in the hundreds.

The system provides a natural method to incorporate hierarchical information into the analysis. The hierarchical information comes from the interrelationships given by the nodes through the inheritance property of frames. The relational information such as object-1 is left of object-2 is expressed in the frames. There is an emphasis in this vision system for gathering independent evidence related to the presence of objects. This means that one needs a method for combining independent information sources and obtaining a belief in the presence of the object based upon all the available information[Shafer 1976]. A belief maintenance system is needed to combine the information obtained from the different sources. Several systems have been proposed some of which are heuristic and some have a theoretical basis. Fuzzy logic and the Dempster-Shafer theory are examples of systems with a theoretical base. It is felt that a reasonable choice of a belief maintenance is the Dempster-Shafer system. We have conducted extensive investigations with this system and with our operators in the analysis of aerial scenes[Harlow et. al. 1985, Connors et. al. 1984]. The results show promise in developing new insights into vision systems.

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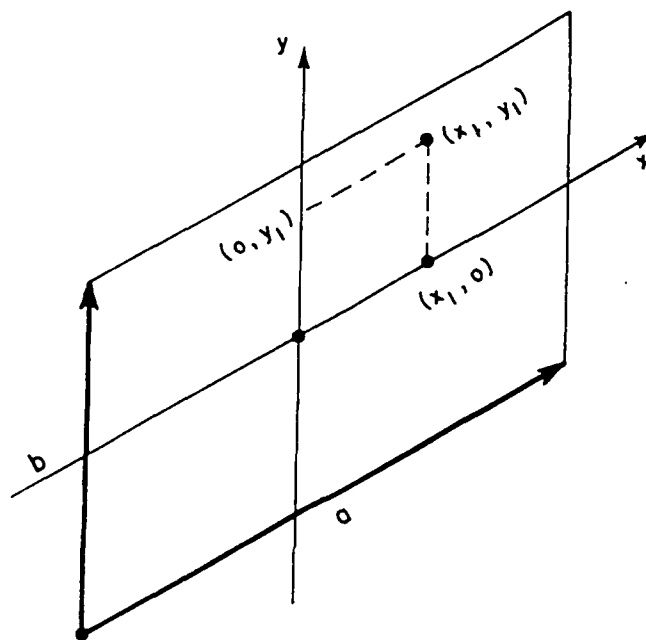
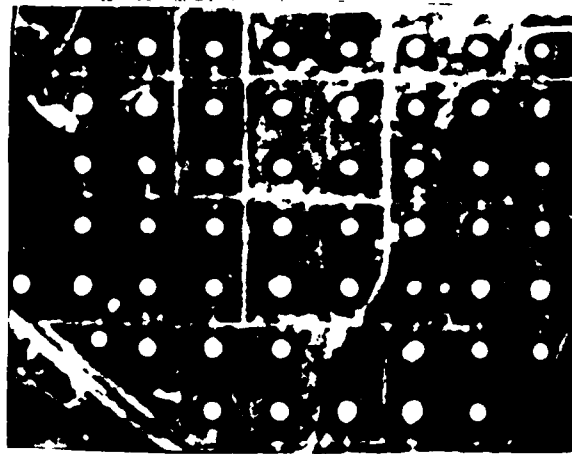
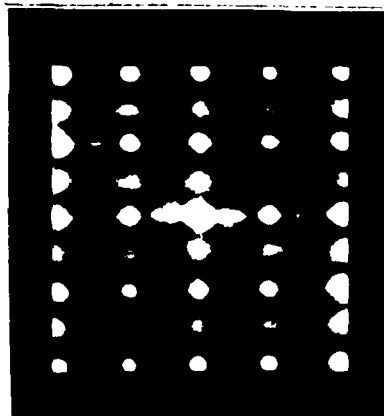


Figure 1. A parallelogram centered coordinate system. The origin is at the center of the parallelogram.



(a)



(b)

Figure 2. Aerial view of an oil storage tank farm in Baton Rouge. Part (a) is the image. Part (b) is the contrast spectrum. High values are shown in white while low values are black. The center point is $(\delta x, \delta y) = (0,0)$.

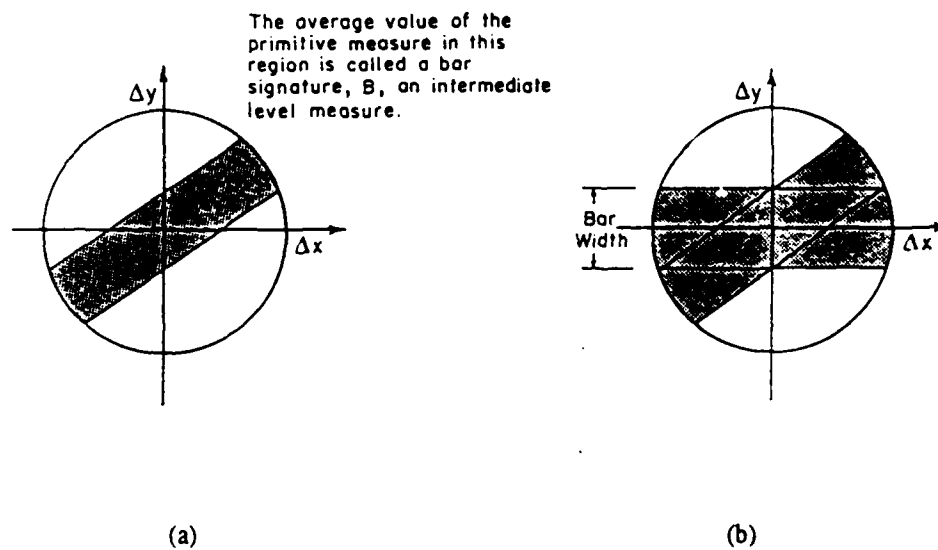


Figure 3. Part (a) A bar measure of a primitive measure spectrum is the average value of the primitive measure over a bar shaped region centered about the origin of the spectrum. Part (b) Multiple bar measures are shown.

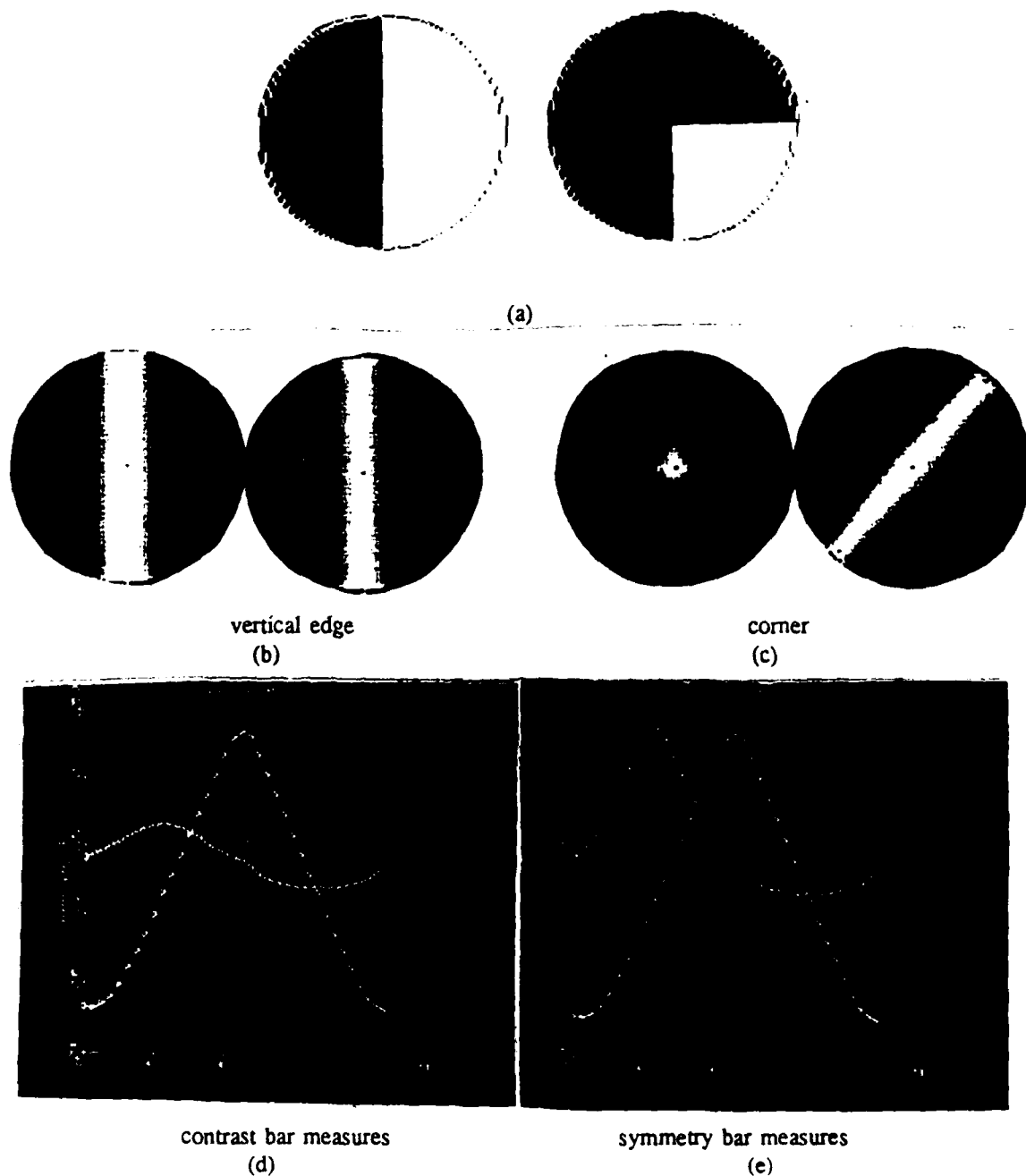
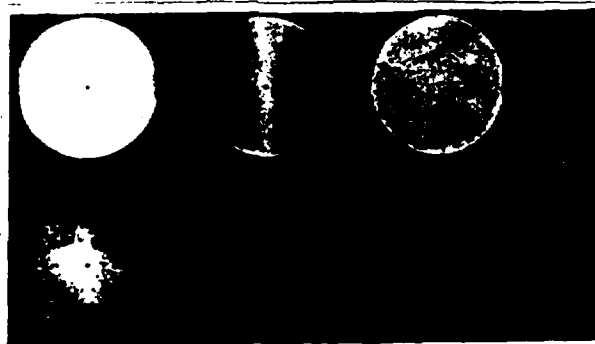


Figure 4. Edge detection using bar measures from the contrast and symmetry spectra. Part (a) shows a binary pattern with two circular areas superimposed. Parts (b) and (c) show images of the contrast(left) spectrum and the symmetry(right) spectra of the regions of (a). Parts (d) and (e) show bar measures as a function of orientation. Part (d) shows the contrast bar measures part (e) shows the symmetry bar measures. The contrast and symmetry bar measures have maxima aligned in the direction of the vertical edge. The symmetry bar measure is a maximum in the direction of the symmetry of the corner region.



(a)



(b)

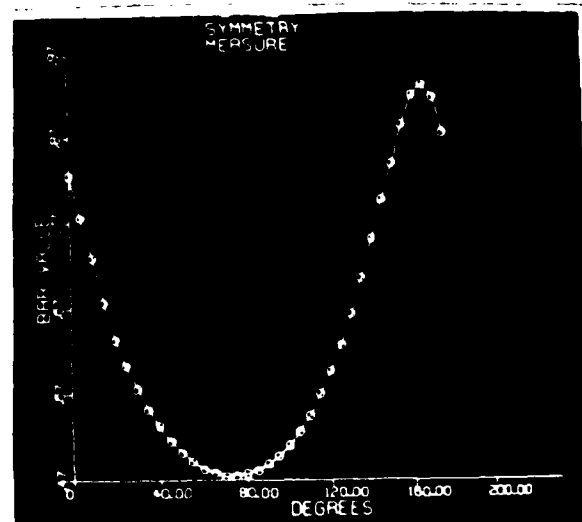
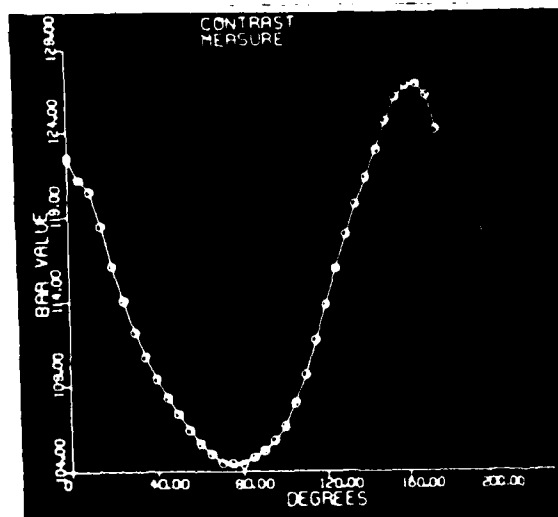


(c)

Figure 5. Edges of Textured Regions. Part (a) shows three areas E1,E2 and E3. E2 is on the boundary between the forested regions and a grassy region. Part (b) shows the contrast and symmetry spectrums for the three regions starting with E1 on the left. Part (c) shows the bar measures for the symmetry and contrast spectrums for the three regions.

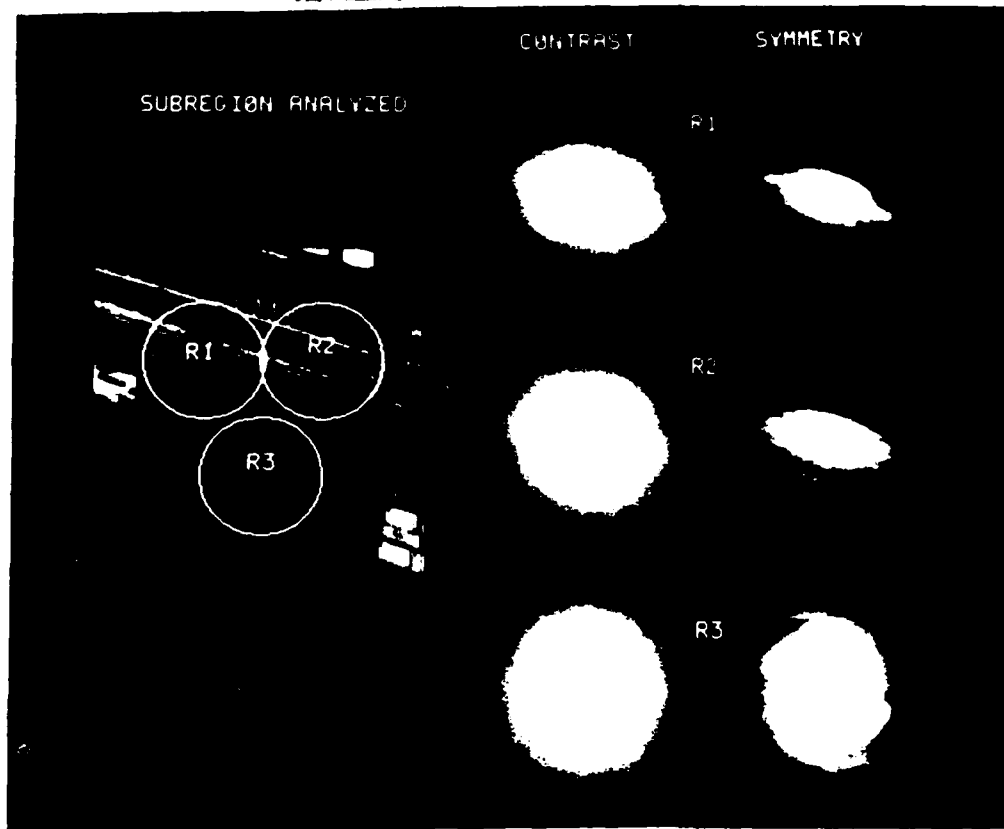


(a)



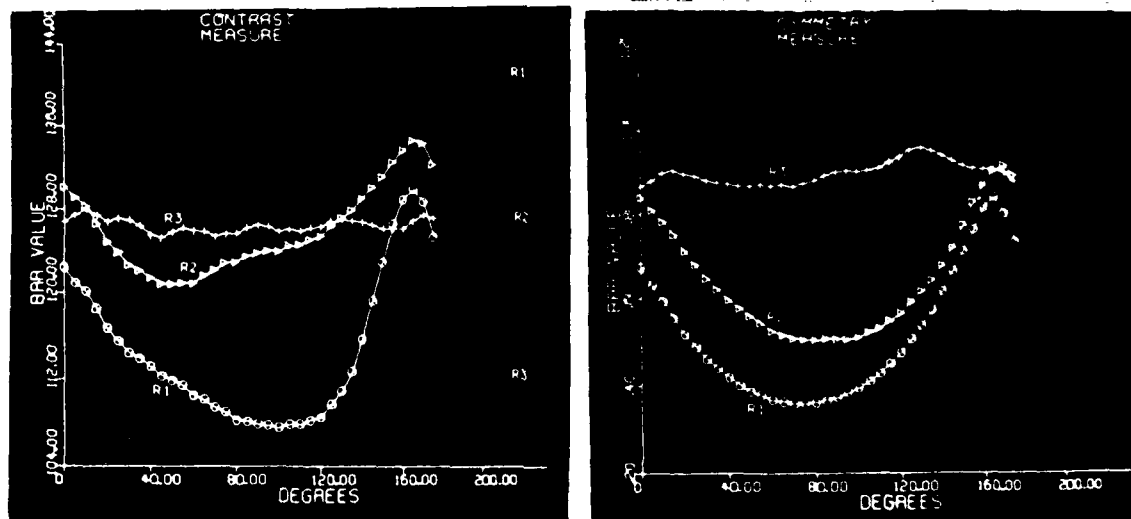
(b)

Figure 6. Linear Features. Part (a) shows a circular region from which spectrums are computed. The region contains a road. Part (b) shows Bar measures for the symmetry and contrast measures. The road orientation is indicated by the maxima in the bar measures.



(a)

(b)



(c)

Figure 7. Road Features. Part (a) shows three circular regions. R1 and R2 have a road in the region. Part (b) shows the contrast and symmetry spectrums. Part (c) shows the bar measures for the contrast and symmetry measures.

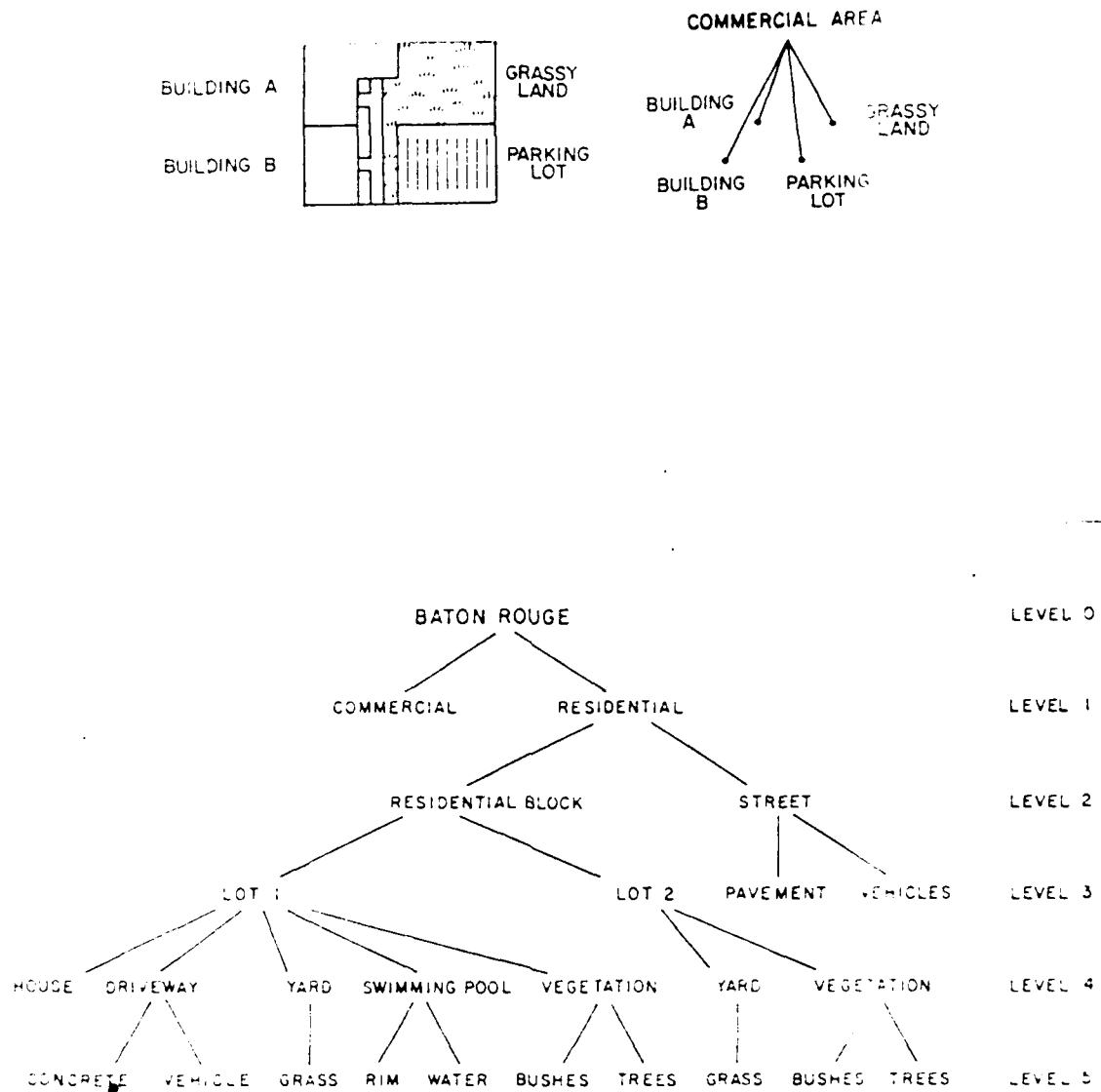


Figure 8.

Example Object Hierarchy.

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